Feature Fusion for Pattern Recognition

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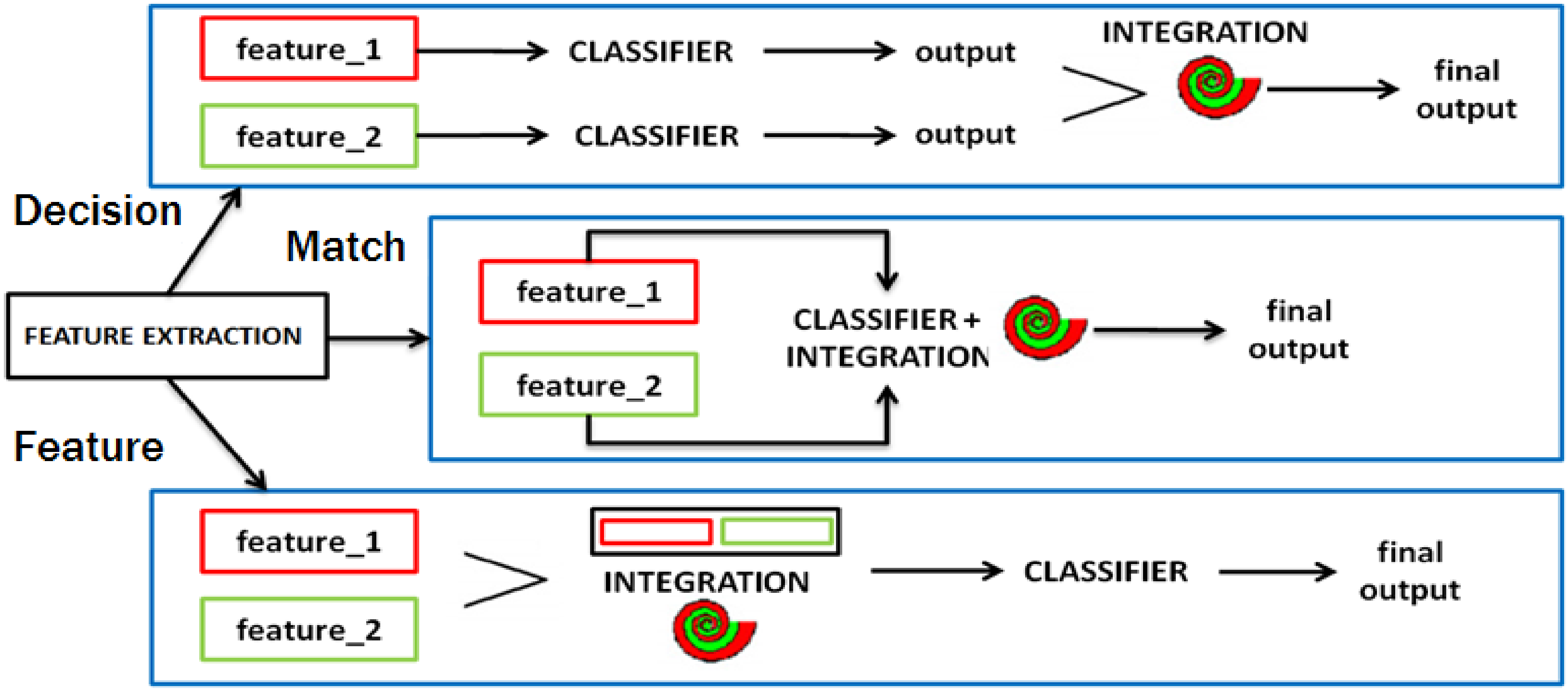
Introduction

- Information or data fusion is one of the solutions adopted for improving the performance of a pattern recognition (PR) system
- In visual recognition, image representations are generally categorized into global and local based types
- Psychological findings have shown that humans equally rely on both local and global visual information
- It is expected that a visual recognition system can benefit from different representations (both local and global) through the use of information fusion

Introduction (Three Levels of Fusion)



- In the literature **Match level** and **Decision level** fusion have been extensively studied, whereas **Feature level** fusion is a relatively understudied problem because of its inherent difficulties

Introduction (Challenges:Feature Level Fusion)

- Directly encoding multiple features may incorporate redundant, noisy or trivial information, which can seriously affect the performances of the recognition process

- The integration of multiple feature sets increase the number of variables used to represent the original data, and the concatenated feature vectors may lead to the problem of curse of dimensionality

- Different feature modalities can have varying (sometime unknown) confidence levels in accomplishing different tasks, multiple modalities may have incompatible feature sets and the relationship between different feature spaces may not be known

- The integration of multiple features comes at a cost, which may incur in units of time, computational resources or even money

Research Motivation

- Despite its challenges, it is thought that data fusion at ***Feature Level*** (lower level) would still retain a richer source of discriminative information

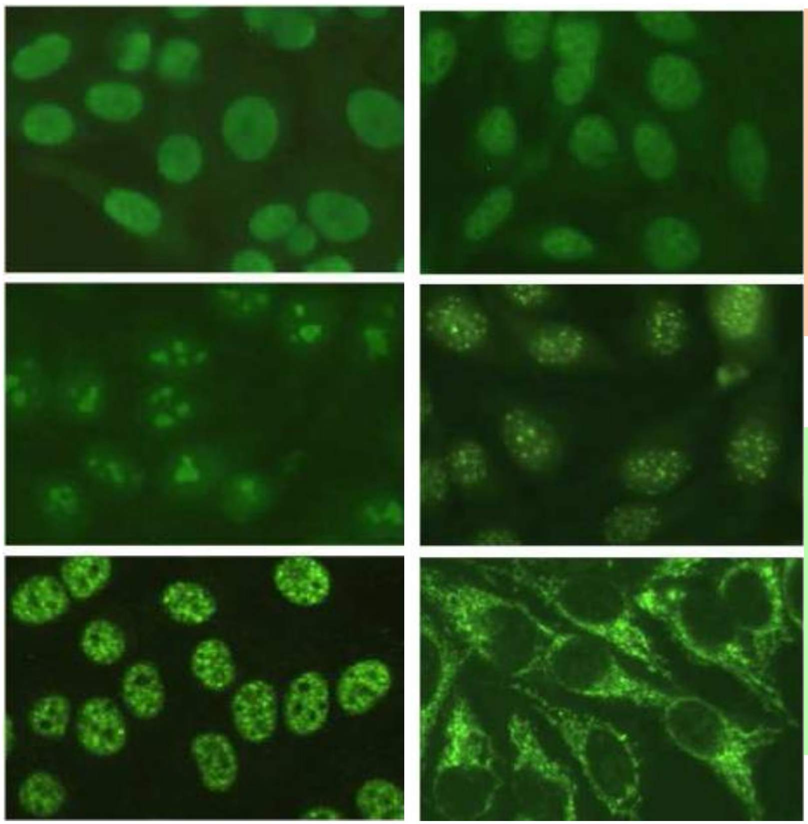
- Motivated by the belief, this thesis work investigated the use of ***Feature Level Fusion*** and its correlation with feature selection and classification tasks for two recent PR problems

  - Classification of HEp-2 staining patterns in ImmunoFluorescence (IIF) images

  - Automatic Identification of Kinship relations from pairs of facial Images

Classification of HEp-2 staining patterns

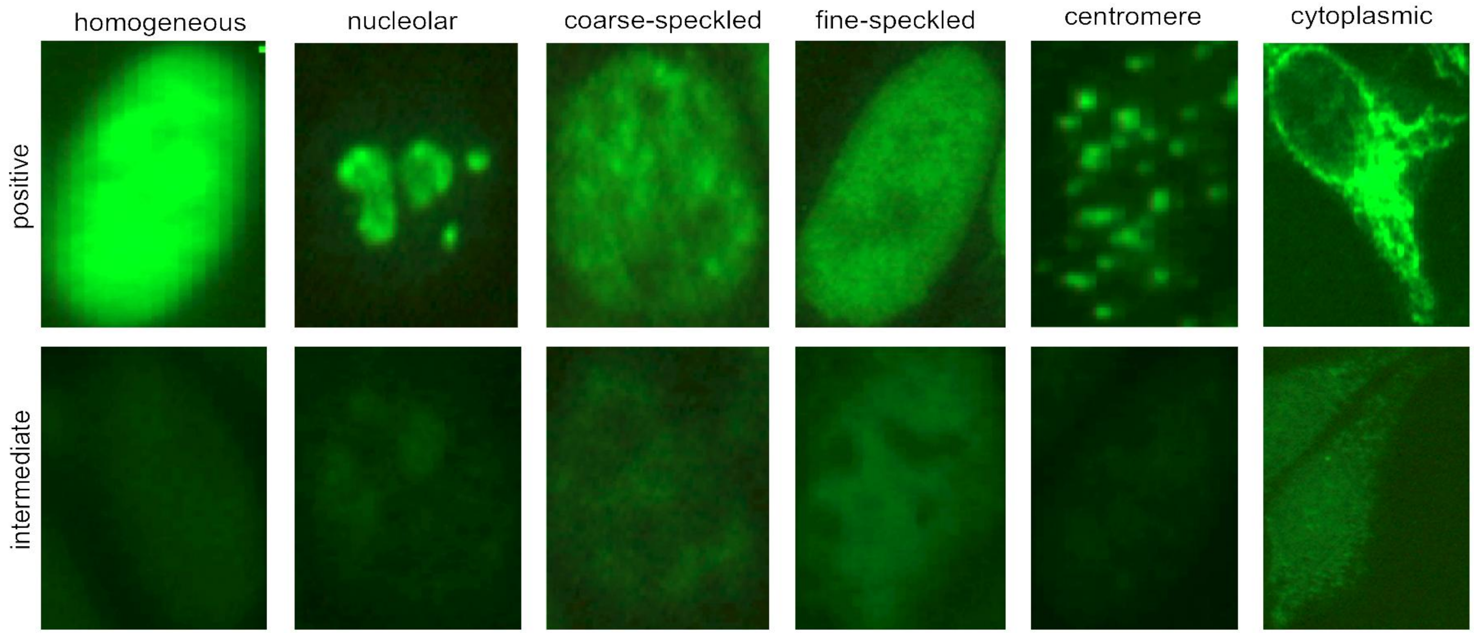
- The analysis of Indirect Immunofluorescence (IIF) HEp-2 cell images is a standard laboratory test, and is important for the differential diagnosis of autoimmune diseases



- Visual evaluation
  - tedious and time-consuming
  - dependent on the subjectivity of the specialist
  - requires highly-specialized and trained operators

- Automated analysis
  - based on standardized quantifiable image features
  - fast processing of large volumes of data
  - requires null or minimal human interaction

Classification of HEp-2 staining patterns (Six –types)



- ***MIVIA HEp-2* Image dataset** (28 images, one per patient)
- Labeled Segmented Cells (1455 individual cells)
- Binary masks describing the region of Interest (ROI)

Classification of HEp-2 staining patterns

Our contribution to the classification of staining patterns is twofold:

- We proposed a set of features to characterize cell images that are highly discriminative with respect to their fluorescence patterns; such feature set was obtained through a detailed analysis of single image attributes (derived from ***morphological***, ***global*** and ***local texture*** analysis), as well as of their integration at feature level, and of the selection of the most relevant feature variables

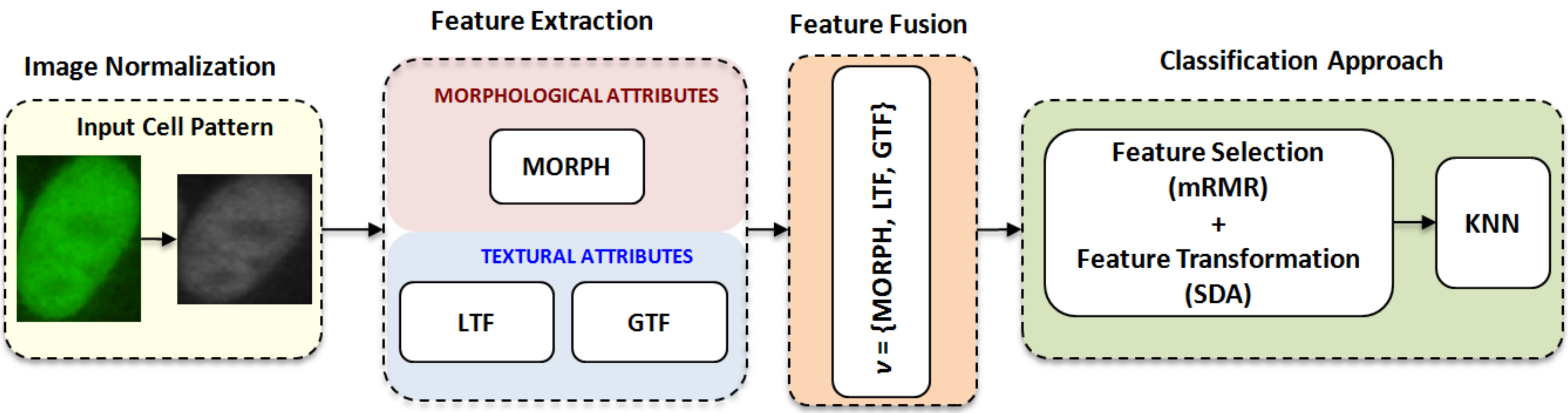
- We proposed a **Subclass Discriminant Analysis** (SDA) based strategy to remap the cell representations into a novel feature space that provides a better separation of the classes aimed at simultaneously improving the intra-class similarities and inter-class dissimilarities and, thus, at making the classification task easier and more accurate.

Classification of HEp-2 staining patterns

Cell Image Representation

- **Morphological features**: focus on shape attributes of the fluorescent signal or of specific regions within the cells
- **Global texture descriptors**: summarize the overall appearance or general distribution of the gray-levels in the cell image
  - Gray-Level Co-occurrence Matrices (**GLCM**)
  - Edge Orientation Histograms (**EOH**)
  - Rotation-Invariant Gabor features (**RIGF**)
  - Modified Zernike moments (**ZERN**)
- **Local texture descriptors**: summarize the isolated contribution of small regions or pixel neighborhoods
  - Rotation-Invariant Uniform Local Binary Patterns (**LBP^{riu2}**)
  - Completed Local Binary Patterns (**CLBP)**
  - Co-occurrence of adjacent LBPs (**CoALBP)**
  - Rotation-invariant Co-occurrence of adjacent LBPs (**RIC-LBP)**

Classification of HEp-2 staining patterns

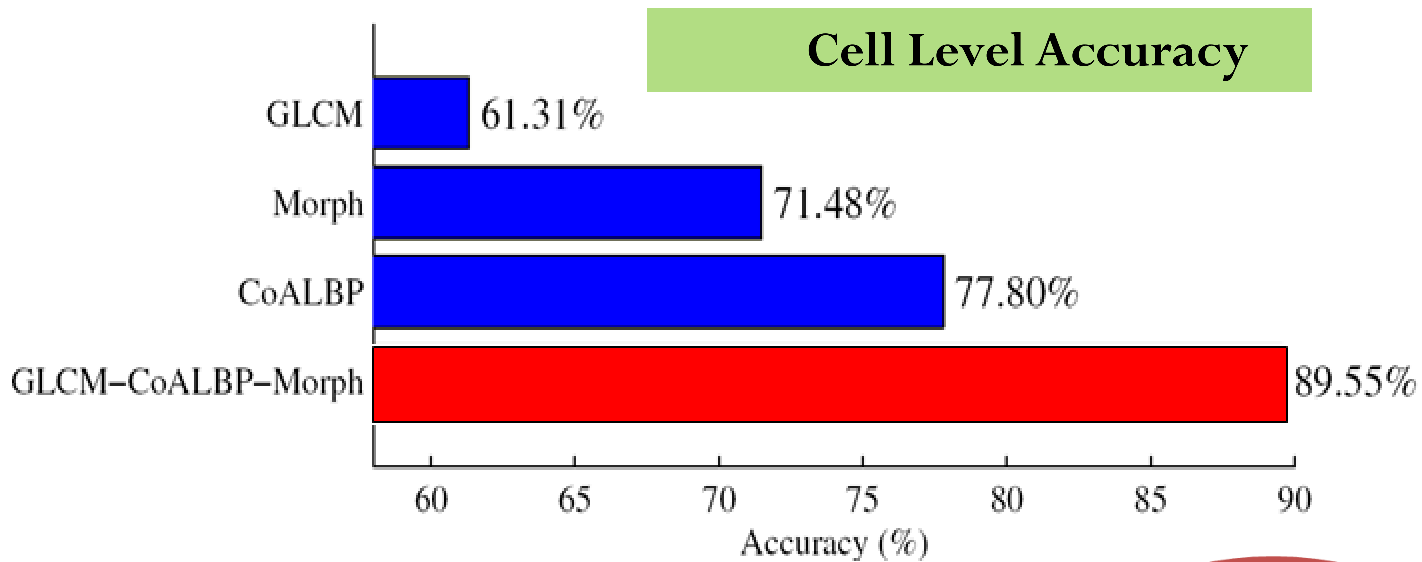


- Size Normalization (128x128)
- Contrast Normalization

- Morphological (**MORPH**)
- Global Textural Features (**GTF**)
- Local Textural Features (**LTF**)

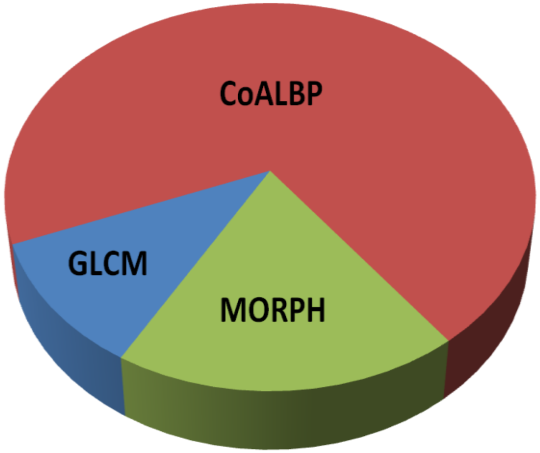
- Minimum Redundancy Maximum Relevance **(mRMR):** Ranks the features based on simultaneous minimization of their mutual similarity and maximization of their relevance with respect to the classification variable
- SubClass Discriminant Analysis **(SDA):** Describes different distributions by modeling each class using a mixture of Gaussians. This is achieved by dividing the classes into subclasses.

Classification of HEp-2 staining patterns

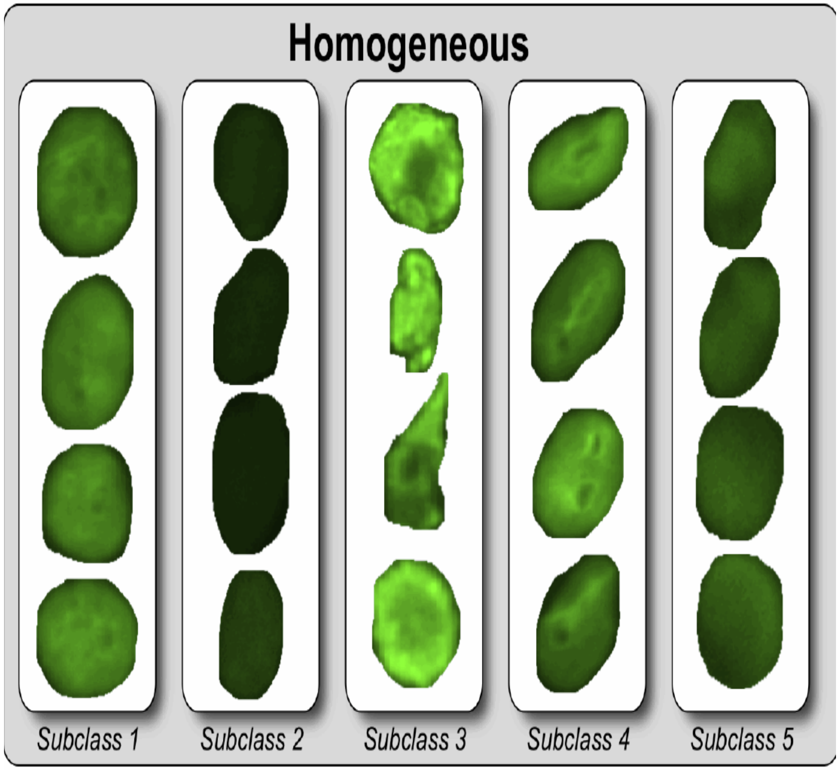


Feature Selection (mrmr)

Distribution of features in: **GLCM-CoALBP-MORPH**



Classification of HEp-2 staining patterns



Feature Transformation (SDA)

Five subclasses identified by **SDA** for the (Homogeneous) class

Classification of HEp-2 staining patterns

Relavant Publications:

Journal Papers

- S. Di Cataldo, A. Bottino, **Ihtesham Ul Islam**, T.F. Vieira, E. Ficarra (2014) ***Subclass Discriminant Analysis of Morphological and Textural Features for HEp-2 Staining Pattern Classification.*** In: PATTERN RECOGNITION, vol. 47, pp. 2389-2399. - ISSN 0031-3203

Books Chapters

- **Ihtesham Ul Islam**, S. Di Cataldo, A. Bottino, E. Macii, E. Ficarra ***A preliminary analysis on HEp-2 pattern classification.*** In: Biomedical Engineering Systems and Technologies / M.F. Chimeno et al. Springer, Berlin Heidelberg.

Conference Papers

- **Ihtesham Ul Islam**, S. Di Cataldo, A. Bottino, E. Ficarra, E. Macii (2013) ***Classification of HEp-2 staining patterns in ImmunoFluorescence images. Comparison of Support Vector Machines and Subclass Discriminant Analysis strategies.*** In: BIOINFORMATICS (International Conference on Bioinformatics Models, Methods and Algorithms) 2013, Barcelona (SP), 11-14 February 2013. pp. 1-9

Automatic Identification of Kinship relations from pairs of facial Images

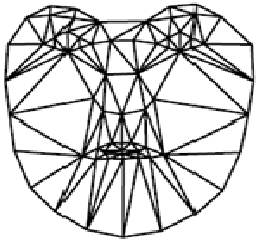
- The automatic Kinship Verification (KV) consists in telling whether two individuals are related or not, based on the analysis of their facial images
- KV applications include family photos organization, finding missing family members, security, preventing child trafficking and forensics
- A challenging task which has to deal with:
  - differences in race, age and gender of the subjects
  - different Degrees of facial similarity
  - conditions of the available facial images

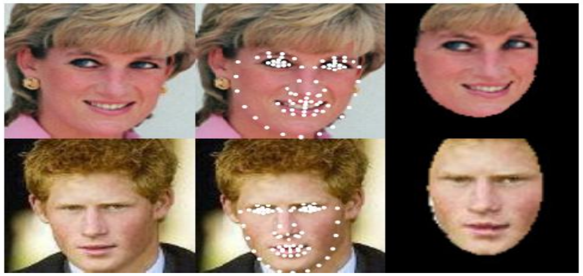
- **Kinship Image Datasets**
  - KV Dataset
  - UB Kinface
  - KinFaceW-II

Automatic Identification of Kinship relations from pairs of facial Images

Kin-Face Image Representation

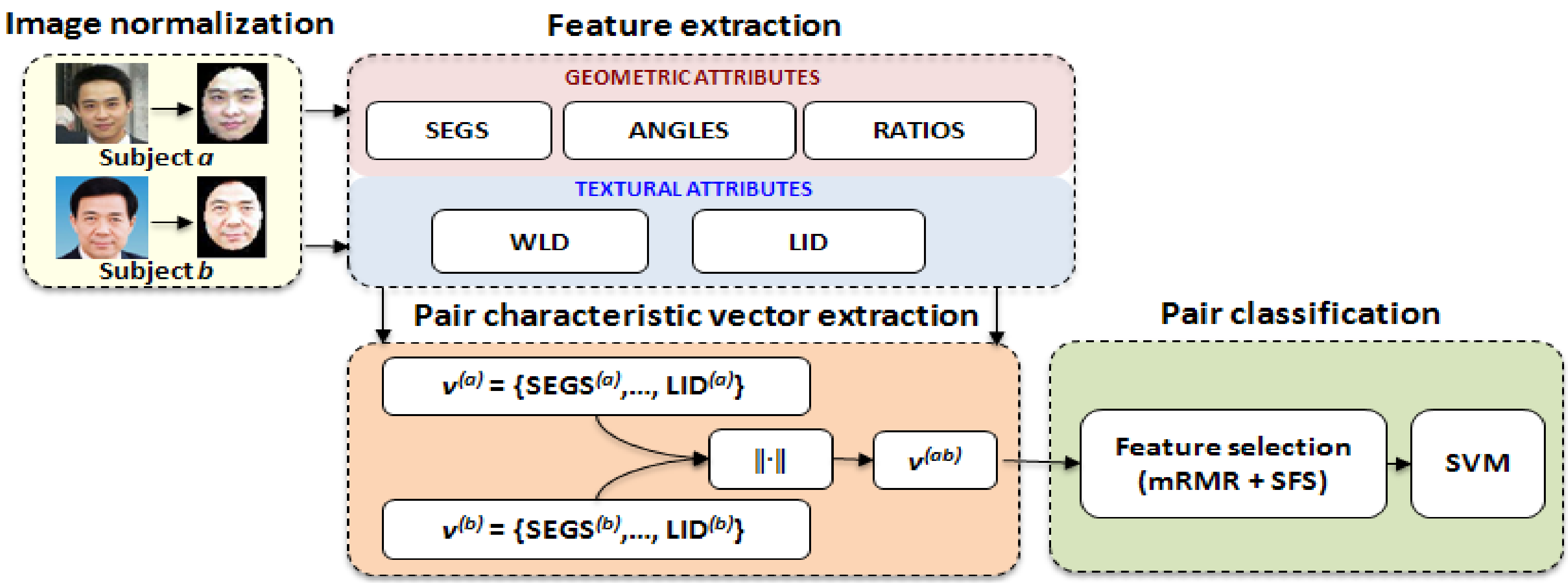
- **Geometric Attributes:** focusing on shape features computed from the position of 76 facial landmarks;
  - SEGS (184 lengths of the DT segments),
  - ANGLES (342 angles of the triangles obtained from DT),
  - RATIOS (862 ratios of pairs of DT segments sharing the same vertex)



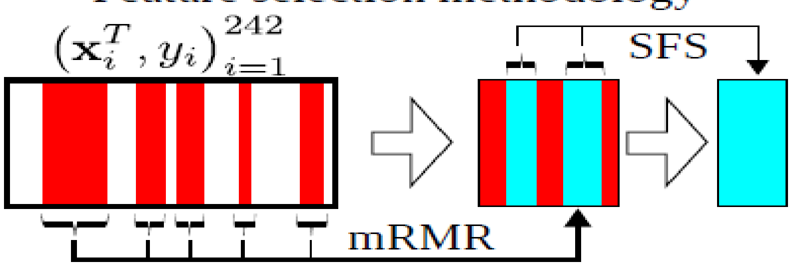


- **Textural Attributes:** summarizing texture features of the whole image or of small regions surrounding landmarks.
  - **Local Image Descriptor (LID):** SIFT-based descriptors have been used to characterize the regions surrounding facial landmarks, 384 size vector.
  - **WLD:** is based on the Weber's law, which summarizes the image texture globally. 2880 elements feature histogram.

Automatic Identification of Kinship relations from pairs of facial Images



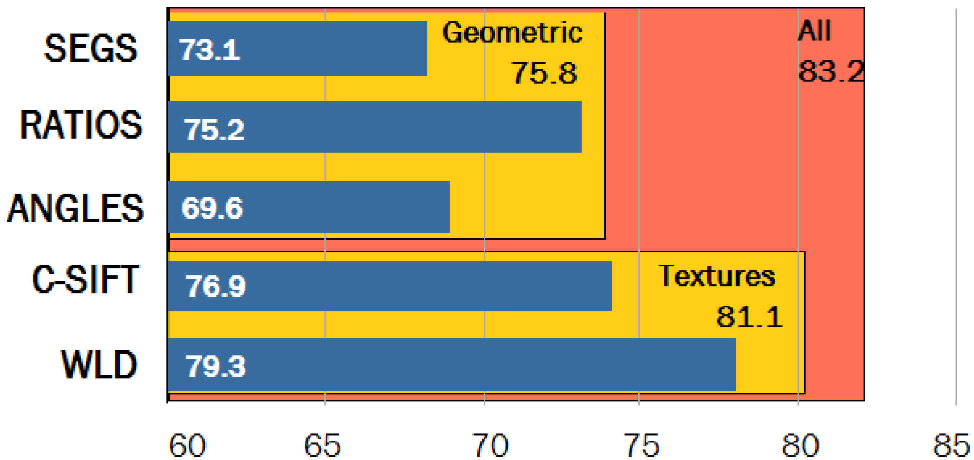
Feature selection methodology

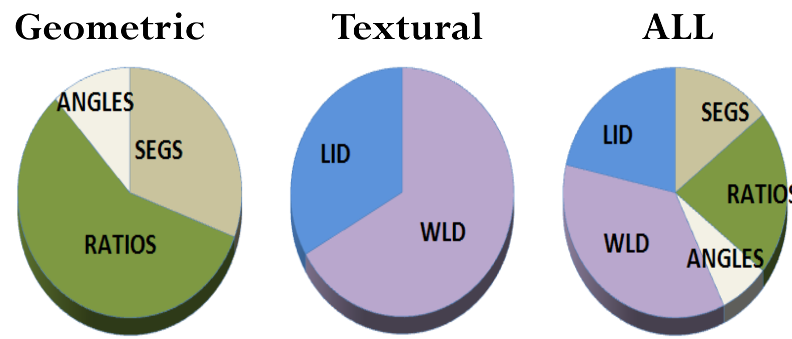


- min-Redundancy Max-Relevance (**mRMR**)
- Sequential Forward Selection (**SFS**)
- Support Vector Machine (**SVM**)

Automatic Identification of Kinship relations from pairs of facial Images

Pair classification Accuracies (%) on KV Dataset





Distribution of features after Two-Step Feature Selection

	Accuracy(%)
Human Panel	67.2
Fang et al.	70.7
Lu et al	71.6
Our Method	**83.2**

Classifier	Accuracy(%)
RDF	77.5
BTrees	78.5
KNN	79.1
SVM	**83.2**

Automatic Identification of Kinship relations from pairs of facial Images

Using ALL Attribute group

KinFace-II Dataset

	Accuracy(%)
Human Panel	74.0
MNRML	76.5
Our Method	81.5

UB Kin Dataset

	Accuracy(%)	
	Set1	Set2
Human Panel	56.0	NA
TSL	60.0	NA
MNRML	67.3	66.8
Our Method	70.3	70.5

Automatic Identification of Kinship relations from pairs of facial Images

Cross DataBase Experiments Using ALL Attribute group

KV Dataset as Train Dataset

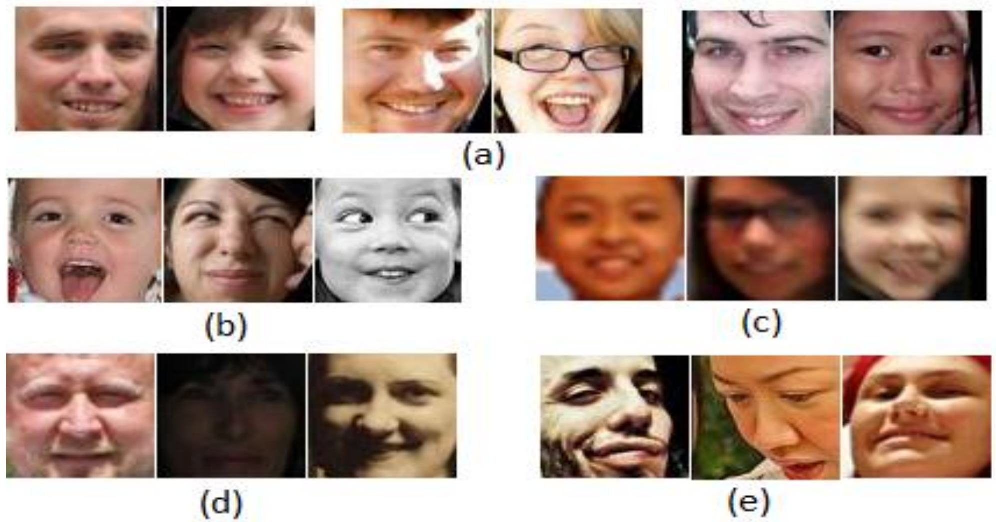
Test DataSet	Cross-DB acc. (%)	Within-DB acc. (%)
UB Kinface Set 1	70.0	70.3
UB Kinface Set 2	68.8	70.5
KinFaceW-II	76.6	77.8

KV Dataset as Test Dataset

Train DataSet	Cross-DB acc. (%)
UB Kinface Set 1	77.3
UB Kinface Set 2	74.9
KinFaceW-II	79.7

Automatic Identification of Kinship relations from pairs of facial Images

- International Evaluation on **Kinship Verification in the Wild** (KVW 2015)



- **Textural Descriptors**
  - Local Phase Quantization **(LPQ)**
  - Three-Patch LBP (**TPLBP**)
  - Weber descriptor (**WLD**)

Automatic Identification of Kinship relations from pairs of facial Images

DataSet-1

	Accuracy(%)
Human Panel	63.8
ULPGC	70.0
BIU	79.3
LIRIS	82.7
NUAA	83.0
Our Method	**86.3**

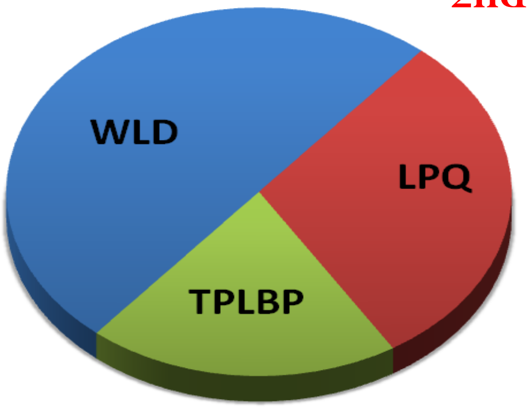
1st !

DataSet-2

	Accuracy(%)
Human Panel	66.8
ULPGC	80.0
BIU	80.9
NUAA	82.5
LIRIS	86.0
Our Method	**83.1**

2nd !

Feature Distribution
TPLBP-LPQ-WLD



Automatic Identification of Kinship relations from pairs of facial Images

Relavant Publications

Journal Papers

- A. Bottino, T.F. Vieira, **Ihtesham Ul Islam** (In Press), ***Geometric and Textural Cues for Automatic Kinship Verification***. In: INTERNATIONAL JOURNAL OF PATTERN RECOGNITION AND ARTIFICIAL INTELLIGENCE. - ISSN 0218-0014

Conference Papers

- A. Bottino, **Ihtesham Ul Islam**, T.F. Vieira (**accepted**), ***A Multi-perspective Holistic Approach to Kinship Verification in the Wild***, In: International Workshop on Biometrics in the Wild, in conjunction 11th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2015), Ljubljana, Slovenia
- Jiwen Lu, Junlin Hu, Venice Erin Liong, Xiuzhuang Zhou, Andrea Bottino, **Ihtesham Ul Islam**, et al. (2015), ***The FG 2015 Kinship Verification in the Wild Evaluation***. In: 11th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2015), Ljubljana, Slovenia
- T.F. Vieira, A. Bottino, **Ihtesham Ul Islam** ***Automatic Verification of Parent-Child Pairs from Face Images.*** In: CIARP 2013, Havana, Cuba, 20-23 November, 2013. pp. 326-333

Conclusion

- Data Fusion at ***Feature Level*** retains a richer source of discriminative information
- The integration of suitable sets of features, at the feature level, provides higher performance than when the features are used individually
- The higher the heterogeneity of the features used, the better the performance
- The use of a proper feature selection scheme, feature transformation or both along with the choice of a suitable classifier is crucial in case of ***Feature Level Fusion***
- A comparative analysis of our experimental results with other methods in the literature, on same data-sets, signifies the importance of our proposed methodology

Future Work

- Develop similar approaches based on ***Feature Level Fusion*** for other recent applications such as Fingerprint Liveness detection and Face Anti-Spoofing

- Utilize ***Feature Level Fusion*** in the context of some recent Pattern Recognition frameworks e.g. multi-task learning, sparse coding and deep-learning

- Perform improvements to our current work
  - Implement a complete solution tackling all the steps of an automated IIF image analysis
  - Investigate a multi-class problem of simultaneously identifying different degrees of kinship
  - Analyze how factors such as ethnicity, expressions, gender and age affect a Kinship predictor, and possible approaches to alleviate such influences

Thank you for your attention!